Learning Efficient Multi-Agent Cooperative Visual Exploration

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Visual indoor exploration with multiple agents, where the agents need to cooperatively explore the entire indoor region using as few steps as possible.
Framework (MAANS)

Neural SLAM module outputs agent-centric local map and the pose estimation.
Framework (MAANS)

Map Refiner unifies the map representation.
Framework (MAANS)

Spatial Coordination Planner (SCP) applies a transformer-based relation encoder and a spatial action decoder.
The local planner performs trajectory planning; The local policy generates actions.
Spatial Coordination Planner (SCP)
Spatial Coordination Planner (SCP)

Each agent’s input map
Spatial Coordination Planner (SCP)

NCNN-based feature extractors obtain a $8 \times 8$ feature map.
Spatial Coordination Planner (SCP)

Transformer-based relation encoder capture the intra-agent interactions.
Spatial Coordination Planner (SCP)

Spatial action decoder captures the spatial structure.
Map Refiner and Map Merger
Map Refiner and Map Merger

Map Refiner:
- Map Composition
- Coordinate Transformation
- Map Enlargement

Map Merger:
- Map Refiner
  - Map Composition
  - Coordinate Transformation
  - Map Enlargement

Agent 1:
- Agent-centric Local Map
- Agent-centric Global Map
- Refined Global Map
- Map Fusion
- Merged Global Map

Agent k:
- Agent-centric Local Map
- Agent-centric Global Map
- Refined Global Map

Agent N:
- Agent-centric Local Map
- Agent-centric Global Map
- Refined Global Map
Map Refiner

Composes the local maps to recover the agent-centric global map
Map Refiner

Transforms the coordinate system based on the pose estimates
Map Refiner

- **Agent 1**
  - Agent-centric Local Map → Map Composition → Agent-centric Global Map → Coordinate Transformation → Normalized Global Map → Map Enlargement → Refined Global Map

Crops the **unexplorable boundary** and enlarges the house region
Map Refiner and Map Merger
2-agent-setting training performance
Average training performance on trained maps

<table>
<thead>
<tr>
<th>Methods</th>
<th>ACS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest APF</td>
<td>102.79(1.55)</td>
</tr>
<tr>
<td>Utility</td>
<td>105.62(0.89)</td>
</tr>
<tr>
<td>RRT</td>
<td>112.21(1.39)</td>
</tr>
<tr>
<td>MAANS</td>
<td>130.59(1.53)</td>
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</table>

<table>
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<tr>
<th>Behavior Statistics</th>
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<tbody>
<tr>
<td>Cov. Ratio</td>
</tr>
<tr>
<td>------------</td>
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<tr>
<td>0.91(0.01)</td>
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<tr>
<td>0.90(0.01)</td>
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<tr>
<td>0.92(0.01)</td>
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<tr>
<td>0.96(0.00)</td>
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</table>

RRT produces the best result among planning-based methods.

MAANS outperforms RRT with a clear margin.
Exploration Comparison in 2-agent Training

RRT V.S. MAANS
Middle Map Colebrook

RRT
Overlap: 0.63
Steps: 188.72
Ratio: 0.98
ACS: 118.71

MAANS
Overlap: 0.45
Steps: 133.99
Ratio: 0.98
ACS: 141.86

More efficient global goal
Large Map Delton

RRT
Overlap: 0.60
Steps: 235.24
Ratio: 0.93
ACS: 106.87

MAANS
Overlap: 0.49
Steps: 171.77
Ratio: 0.95
ACS: 133.20

More efficient global goal
3-agent-setting training performance
Average training performance on trained maps

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<tr>
<th>Methods</th>
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<tr>
<td></td>
<td></td>
<td>Cov. Ratio</td>
<td>Steps</td>
<td>Over. Ratio</td>
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<tr>
<td>Nearest</td>
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<tr>
<td>Utility</td>
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<td>0.94(0.00)</td>
<td>180.82(2.25)</td>
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<td>RRT</td>
<td>127.64(1.31)</td>
<td>0.95(0.01)</td>
<td>155.13(3.26)</td>
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<tr>
<td>MAANS</td>
<td>143.09(0.71)</td>
<td>0.96(0.00)</td>
<td>132.95(1.86)</td>
<td>0.35(0.02)</td>
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</table>

**RRT** produces the best result among planning-based methods. **MAANS** still produces the best final coverage ratio, the fewest steps, the least overlap ratio and the highest ACS.
Exploration Comparison in 3-agent Training

RRT V.S. MAANS
Middle Map Colebrook

RRT
Overlap: 0.44
Steps: 155.13
Ratio: 0.95
ACS: 127.64

MAANS
Overlap: 0.35
Steps: 132.95
Ratio: 0.96
ACS: 143.09

More efficient global goal
2-agent-setting evaluation performance
A simple training-and-distillation policy, **MAANS-TD**, can work on multiple maps and eventually **generalize to unseen maps**.
Average evaluation performance on unseen maps

<table>
<thead>
<tr>
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<th>Cov. Ratio</th>
<th>Steps</th>
<th>Over. Ratio</th>
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<tbody>
<tr>
<td>Nearest</td>
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<tr>
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<td>MAANS-TD</td>
<td>137.60</td>
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<td>0.58</td>
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**RRT** produces the best result among planning-based methods. **MAANS-TD** achieves the best final coverage ratio, the fewest steps and a comparable overlap.
Exploration Comparison in 2-agent Evaluation

RRT V.S. MAANS-TD
Unseen Map *Nicut*

**RRT**
- Overlap: 0.60
- Steps: 217.98
- Ratio: 0.93
- ACS: 109.46

**MAANS-TD**
- Overlap: 0.56
- Steps: 213.44
- Ratio: 0.93
- ACS: 120.64

More efficient global goal
Thanks

Visit our website for more information

MAANS

https://sites.google.com/view/maans

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